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PRINCIPAL INVESTIGATOR: Xiao Han

CONTRACTING ORGANIZATION: UNIVERSITY OF CHICAGO
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6. AUTHOR(S)
Xiao Han
Betty Diamond

E-Mail: xiaohan@uchicago.edu

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14. ABSTRACT
Adaptive radiotherapy (RT) is an advanced technique for prostate cancer treatment which employs kilovoltage (KV) cone-beam CT (CBCT) for guiding treatment. High quality CBCT images are important in achieving improved treatment effect, but they also require a non-negligible amount of imaging radiation dose which raises patient safety concern. Therefore, the goal of this project is to investigate and develop innovative, prior-image-based CBCT imaging techniques that can yield high quality images with reduced dose. During the second year of this project, I have investigated and implemented novel scanning trajectories with aid of additional hardware components and software control. I carried out a rigorous investigation on developing optimization-based image reconstruction algorithms by specifying a discrete imaging model, formulating optimization programs, and designing and implementing iterative algorithms. Prior images have been investigated for incorporation in image reconstruction tasks for all the data acquisition configurations. Quantitative metrics have been calculated for quantitatively characterizing and evaluating the reconstruction quality, choice of parameters, and strategies for incorporating prior images. The research that I carried out during the second year was as planned in the proposal, and the results built a solid basis for continuing further investigation planned for the next year.

15. SUBJECT TERMS
Cone-beam Computed Tomography, Adaptive Radiation Therapy, Radiation Dose

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INTRODUCTION

Prostate cancer is the most common non-skin cancer and the second leading cause of cancer death among American men [1]. Modern radiotherapy of prostate cancer relies heavily on imaging technologies for accurate patient setup and target localization [2]. In adaptive radiation therapy (RT) [3], one of the most advanced RT techniques, the treatment plan is adaptively adjusted according to the tumor's change in position, size, and shape [4-6]. Therefore, high-quality 3D images with good soft-tissue contrast are necessary for achieving successful adaptive RT. Kilovoltage cone-beam CT (CBCT) has shown its capability of yielding such images to guide the prostate cancer treatment [7-8]. However, frequent use of high quality CBCT images is often associated with a substantial amount of imaging radiation dose [9-12], which raises concerns about patient safety. On the other hand, one unique feature of clinical CBCT is the availability of a high-quality diagnostic CT image, which can be incorporated in the CBCT image reconstruction as prior knowledge. The objective of this project is to investigate and develop advanced CBCT imaging techniques that utilize prior images for optimized image quality and reduced imaging dose. In the past year, my effort in the proposed project have been supported by a Predoctoral Trainee Award, and I have carried out research tasks as planned. As discussed below, I have investigated and implemented novel scanning trajectories with aid of additional hardware components and software control. Simulation data have been generated for initial test of object coverage for these scanning trajectories. I have also acquired real data of physical phantoms by using a clinical CBCT system under a variety of sampling configurations, including full-view, sparse-view, truncated data, and offset-detector configurations. I carried out a rigorous investigation on developing optimization-based image reconstruction algorithms by specifying a discrete imaging model, formulating optimization programs, and designing and implementing iterative algorithms. I have designed a host of parameters for the imaging model, optimization programs, and iterative algorithms, and strategies for adaptively selecting these parameters have been laid out. I have used optimization-based algorithms developed to reconstruct images from data acquired under various sampling configurations. Prior images have been investigated for incorporation in image reconstruction tasks for all the data acquisition configurations. Quantitative metrics have been calculated for quantitatively characterizing and evaluating the reconstruction quality, choice of parameters, and strategies for incorporating prior images. The research that I carried out during the second year was as planned in the proposal, and the the results built a solid basis for continuing further investigation planned for the next year.

BODY

1 Research Accomplishments

1.1 Investigate and implement novel scanning trajectories

I have investigated and implemented non-conventional scanning trajectories for the clinical CBCT system. The current CBCT systems employ flat-panel detectors, which have limited size, and lack a slip-ring device as available on most diagnostic CT systems. Therefore, the standard circular trajectory as the only choice available on most clinical CBCT systems result in a limited axial field of view (FOV), which poses challenges in clinical applications when the CBCT images are registered to the planning CT images with a significantly larger axial coverage. Specifically, I investigated two possible solutions to extending axial coverage, a reverse-helix trajectory and a two-circle trajectory. I first investigated the theoretical axial coverage by using the Tuy's condition [13] and chord-based reconstruction theory [14]. Then, I performed test reconstructions using simulation data generated from a disk phantom and a numerical anthropomorphic phantom [15]. I also considered the implementation feasibility of these trajectories on existing systems available in radiation oncology clinic. Finally both two trajectories were implemented with aid of necessary parts and auxiliary component devices.

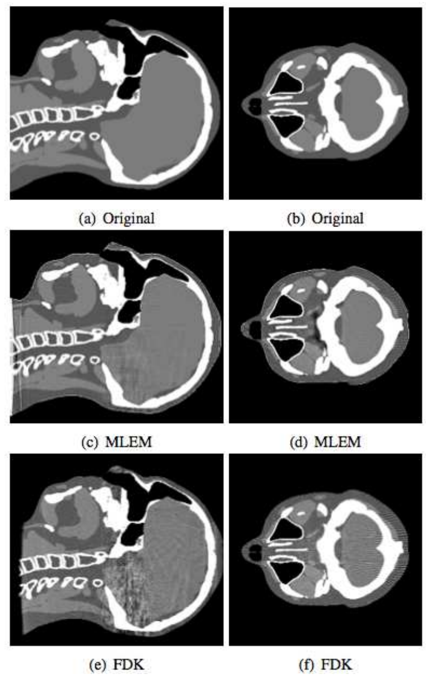

Figure 1: Images of the XCAT phantom within the middle sagittal (a, c, and e) and middle transverse (b, d, and f) slices reconstructed by use of the expectation maximization (EM, c and d) and FDK (e and f) algorithms from the two-circle scanning data. The phantom truth within corresponding slices is displayed in (a) and (b).

Reverse-helix trajectory I first investigated the reverse-helix trajectory, which has been proved to offer larger axial FOV when reconstructed by use of an innovative technique [16]. For practical feasibility, this trajectory can be realized on the clinical CBCT system with minimal additional translational feeder device and associated software control. Then, by continuously feeding in the imaged subject, while rotating the gantry two turns consecutively, first a clock-wise (CW) spin and then a counter clock-wise (CCW) spin, an effective reverse-helix trajectory was obtained. I have obtained the auxiliary devices and software and have them implemented on the clinical CBCT system.

Two-circle trajectory Compared to the reverse-helix trajectory that involves additional hardware device and software synchronization, a two-circle trajectory is more straight-forward to implement. It works by performing a full circular scan, translating the couch for a certain distance, and then performing another full circular scan. To test the extension of axial coverage, I carried out a simulated data study using numerical disk and anthropomorphic XCAT phantoms [15]. As an example, I show in Fig. 1 the reconstruction result of a two-circle scan performed with a longitudinal translation of 10 cm. The reconstruction image within the middle saggital slice demonsrates that enlarged FOV can be achieved by use of the two-circle trajectory in combination with appropriately designed iterative algorithms.

1.2 Investigate and develop the optimization-based algorithms

I have identified three key components for developing optimization-based algorithms for CBCT image reconstruction: specification and analysis of imaging model, formulation of optimization programs, and developing iterative algorithms. Each of the components involve a number of parameters, and effort has been made to developing strategies for choosing parameters appropriate to specific imaging configuration and reconstruction task.

Investigate the discrete CBCT imaging model and data divergence I have carried out detailed analysis on the imaging model of CBCT. The current image-reconstruction algorithms on clinical CBCT systems are based upon a continuous imaging model, whereas the proposed optimization-based reconstructions are derived from a discrete imaging model [17]

$$\mathbf{g_0} = \mathcal{H}\mathbf{f}, \tag{1}$$

which is distinctively different than the continuous model and has significant implications on the potential improvement on data-acquisition flexibility and image reconstruction quality. I investigated the impact of key parameters involved in the imaging model, including the basis vectors for expanding the data and image, as well as the number of pixels and voxels represending the data and image [18]. Based upon the discrete imaging model in Eq. (1), I investigated the choice of data divergence, such as the Euclidean distance or Kullback-Leibler (K-L) divergence, which are defined for quantifying the divergence between the measured data and the model data. I have determined to focus the project on Euclidean distance, because of the availability of numerous algorithms capable of efficiently reducing it. On the other hand, algorithms minimizing K-L divergence have been implemented as reference.

Optimization-program formulation Based upon the imaging model and data divergence, I have designed and investigated a variety of optimization programs for image reconstruction. Specifically, I considered various forms of image regularizations, including ℓ_0, ℓ_1, and total-variation-norms, for incorporation to the optimization programs. Among numerous optimization programs, I have identified and chosen two programs for image-reconstruction in subsequent CBCT experiments [19]:

$$\mathbf{f}^* = \mathrm{argmin}||\mathbf{f}||_{TV} \;\; \text{s.t.} \;\; D(\mathbf{f}) \leq \epsilon \;\; \text{and} \;\; f_j \geq 0, \tag{2}$$

and

$$\mathbf{f}^* = \mathrm{argmin}||\mathbf{f}||_{TV} \;\; \text{s.t.} \;\; D(\mathbf{f}) \leq \epsilon, \; f_j \geq 0, \;\; \text{and} \;\; ||\mathbf{f}||_0 \leq s. \tag{3}$$

The rationale for this choice is that the regularization terms effectively sparsifies the image and reduces the solution set, while iterative algorithms can readily be developed for efficiently reaching the feasible set. Either programs involve a number of parameters, such as the calculation method for image TV and choice of ϵ and s. I have investigated the impact of different choices for these parameters and formed strategies for making reasonable choices according to different reconstruction programs and tasks.

Iterative algorithms Optimization programs in Eqs. 2 and 3, when fully specified with a set of parameters, has each implicitly designed a solution set. Iterative algorithms then need to be employed for numerically arriving at the solution sets. To the best of my knowledge by surveying existing literature of published works, there are no standard iterative algorithms available for converging to the solution sets designed by Eqs. 2 and 3. Therefore, I have designed and implemented a number of iterative algorithms by using the adaptive-steepest-descent-POCS (ASD-POCS) [20,21] framework. The algorithms operate by alternating among several calculation steps. A POCS step is employed for reducing Euclidean distance, a steepest descent (SD) step is used for reducing image TV, and a hard-thresholding step is used for enforcing image positivity and ℓ_0 constraint. In this process, I have accomplished a non-trivial task of selecting algorithm parameters, such that a inter-balance is struck among all the operations, and the whole algorithm approach the designed solution efficiently. Because these parameters depend upon the specific imaging configuration, imaged subject, and reconstruction task, a set of adaptive step-size adjustment scheme has been developed and implemented rather than manually interfering the parameter selection along the iterative computation.

1.3 Validate the optimization-based algorithms

To validate the developed optimization programs and iterative algorithms, I ran the iterative algorithms for solving their respective optimization programs from data consistent with the imaging model [18], which constitutes an ideal scenario. This is an important and necessary step for rigorous algorithm development, because an optimization program and an iterative algorithm are not expected perform well in real data situations if they fail to yield the desired solution in an ideal scenario.

Inverse-crime scenario I have carried out a numerical simulation study for validating the optimization programs and the iterative algorithms. I arranged the simulation under an "ideal" condition, where the simulated noiseless data are generated from a discrete image array using a discrete projector, and the same discrete projector is used also for backprojection during reconstruction. I refer to this well-controlled, ideal condition as an inverse-crime scenario [22], which yields a linear system with, depending on the relation between number of measurements (equations) and voxels (unknowns), one unique or an infinite number of solutions.

Validation against the designed solution The intended outcome of the iterative algorithm is the optimization program's designed solution, i.e., a solution that satisfies all its constraints. I have validated the algorithms with an inverse-crime study by using known numerical phantoms, including the FORBILD [23] and XCAT [15] phantoms. Due to the finite number of iterations and the limited computer precision, it is challenging to evaluate mathematical convergence. Instead, I have computed metrics for each constraint of the optimization program and plotted them against the iteration number, such that the asymptotic behavior is monitored and verified.

Validation against the desired solution Once an algorithm is validated for reaching the feasible set, the reconstructed image represents a "designed solution", which I have validated by characterizing its difference against the ground truth, i.e, the original numerical phantoms, which I refer to as the "desired solution". The results show that for the algorithms under investigation, they all numerically approach, with varying efficiency, to the designed solution; and when the data are sufficient, the designed solution exhibit only numerical difference within computer precision to the desired solution.

1.4 Reconstruct images from fully-sampled CBCT data

I have acquired CBCT data of a physical phantom (Catphan) with a clinical system at the Radiation Oncology Department by using existing scanning protocols. Therefore, the data quality

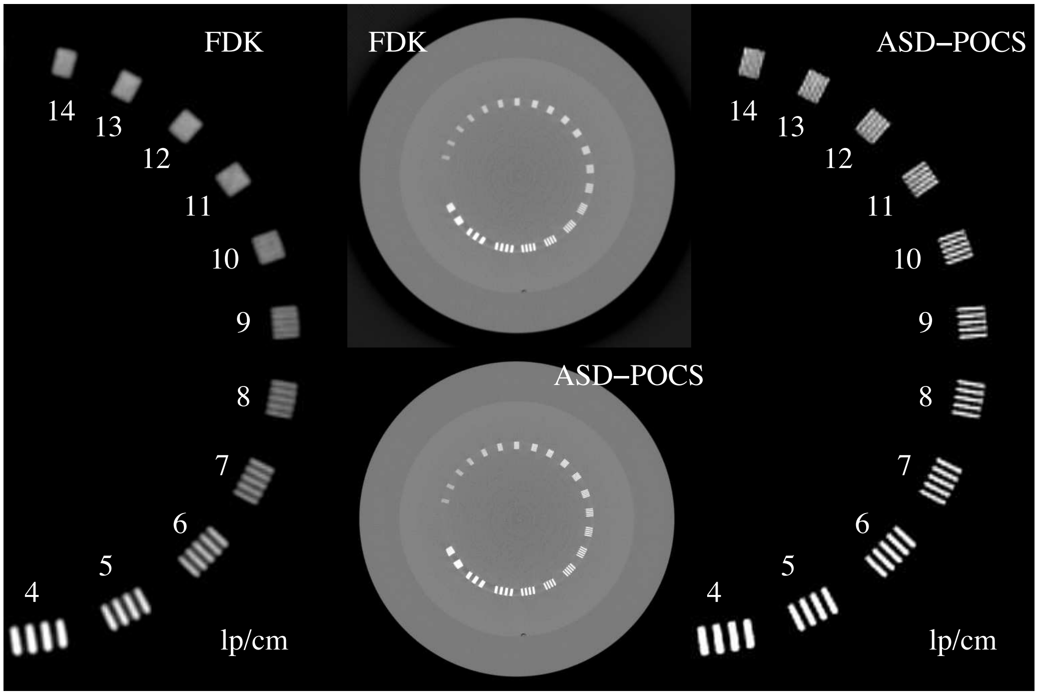

Figure 2: Images of the Catphan phantom within the bar-pattern section reconstructed by use of the FDK and ASD-POCS algorithms from 625-view data acquired with OBI. The display window is [0,0.4] cm^{-1} for the whole section, and [0.25, 0.4] cm^{-1} for the zoomed-in view.

represents what is currently used for quality assurance and clinical applications. The full data sets contain 625 projections, approximately uniformly distributed over the 2π scanning range. The Catphan phantom contains multiple sections, each specifically designed for characterizing one or more specific imaging performance of the CBCT system, including spatial resolution, contrast resolution, and Hounsfield unit (HU) linearity. In an attempt to avoid complications from cone-beam artifact, I have carried out multiple scans by manually aligning the middle plane of each phantom section with the X-ray-source and detector plane. I then applied the optimization-based algorithm to reconstruct images from the acquired data. As a reference, I also reconstructed images by using the FDK algorithm. Result of one representative slice is displayed in Fig. 2. One can observe that the reconstruction obtained with optimization-based algorithm show improved spatial resolution than the FDK reconstruction at similar noise level, which suggests that appropriately developed optimization-based algorithms can potentially used for improving clinical CBCT image quality from data acquired with current configurations.

1.5 Reconstruct images from sparse-view CBCT data

I have acquired sparse-view data of an anthropomorphic (Rando) phantom by using a clinical CBCT system [24]. The original acquisition collected data at 645 views over 2π, from which I uniformly extracted sparse-view data sets containing a subset of projection data, ranging from 64 to 320 views. I have also extracted sparse-view data distributed over a 200-degree range,

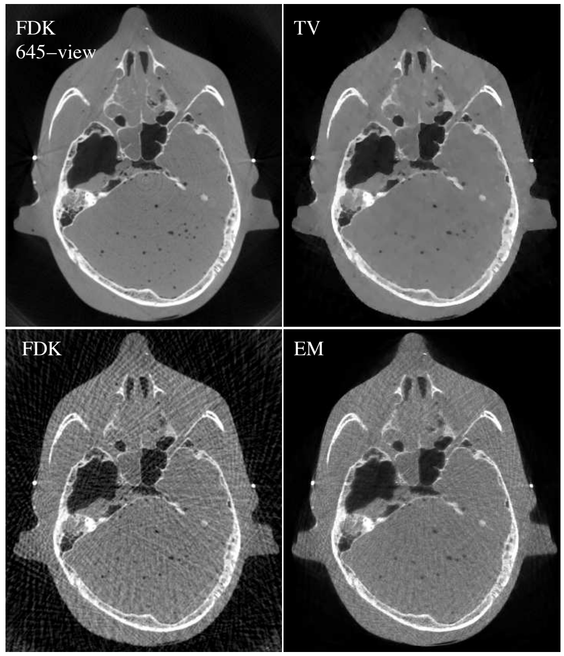

Figure 3: Images of the Rando head phantom reconstructed by use of the TV, FDK, and EM algorithms from a 108-view data set. Also shown is the reference image reconstructed with FDK from the full, 645-view data set.

mimicking the half-scan configuration. By assuming the total patient dose is approximated by the number of projections multiplied by the total number of projections, I have calculated the dose reduction ratios, ranging from 50-90%. I then applied the developed optimization-based algorithm for characterizing its capability of image reconstruction from sparse-view data. For benchmarking purpose, I also reconstructed images from full data using FDK, and from sparse-view data using FDK and expectation maximization (EM) algorithms. I show the reconstructed images within the middle transverse slice in Fig. 3. One can observe that while FDK and EM reconstruction degrade when sparse-view data are used, the optimization-based algorithm was able to reconstruct an image comparable to the full-data FDK reference image. This study shows appropriately developed optimization-based algorithm can potentially be used for sparse-view imaging configuration with significant dose reduction. Furthermore, I have experimented with incorporating a prior image reconstructed from full-data. By performing an affine registration, the intentionally shifted prior image was registered back to the current image and used as an initial estimate for the iterative algorithm. Results show that the incorporation of prior image can further improve the convergence efficiency and lower the required number of projections in the sparse-view data set.

1.6 Reconstruct images from truncated data

I have developed optimization-based algorithms for reconstructing images from data containing truncation [25]. Due to the limited detector size, most body sections, including the pelvis region, of normal-sized patients will cause data truncation, which can severely degrade the quality

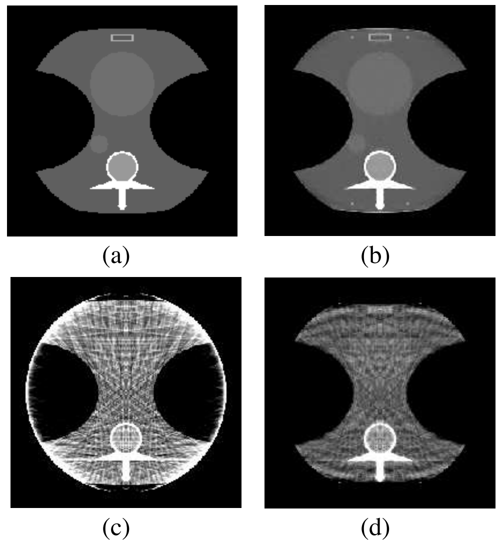

Figure 4: Chest phantom images reconstructed from 60-view simulated projection data with transverse truncation by use of the ASD-POCS (b), FDK (c), and EM (d) algorithms. The ground truth image is displayed in (a). Display window: [0,2] cm^{-1}.

of images obtained with current reconstruction algorithms. I have investigated this issue with a simulated data study. First, I generated a numerical phantom mimicking the patient chest region. The phantom contains both high-contrast structures such as the spine and low-contrast organs such as heart and a soft-tissue tumor. I then simulated the truncated CBCT projection data by forward-projecting the phantom to a detector that is insufficient to cover the entire object. From the truncated data, I applied different algorithms to reconstruct images and compare with the phantom truth. The results are shown in Fig. 4. One can observe that while FDK and EM reconstructions are contaminated by obscuring artifacts and fail to reveal low-contrast objects, the optimization-based reconstruction is comparable to the phantom truth and soft-tissue organs can be clearly identified. The results suggest that the ASD-POCS algorithm can potentially be used in the narrow-beam configuration for yielding high-quality images with significantly reduced patient dose. Furthermore, I have experimented with incorporating a prior image reconstructed from full-data. The affine-registered prior image was used as an initial estimate for the iterative algorithm. Results show that the incorporation of prior image can improve the convergence efficiency and increase the upper bound of allowable degree of data truncation for accurate image reconstruction.

1.7 Reconstruct images from offset-detector data

The FOV of clinical CBCT systems can be enlarged by employing an offset detector geometry. However, this geometry causes ring artifact in images reconstructed by use of existing iterative algorithms, which can affect the localization of ROI in clinical CBCT applications. I have investigated the origin of the artifact, and identified the cause to be a different data redundancy than the normal detector geometry. In an attempt to eliminate the ring artifact, I have developed weighting schemes in the data domain to appropriately account for the data redundancy. By experimenting with a number of weighting matrices, I found out that while they all give the same result in inverse-crime study, only one of them gives satisfactory result in realistic situations, and can completely remove the ring artifact [26]. Based upon this weighting matrix, I have further carried out studies for sparse-view reconstruction from offset-detector data. Results show that images comparable to desired solution can be obtained from sparse-view data acquired with offset-detector geometry. In addition, I have also obtained raw data of a pelvis phantom collected with the offset-detector geometry. The preliminary results corroborated that of the simulated data study. In addition, I have again investigated incorporating a prior image in reconstructing current image from offset-detector data. When the prior image was also obtained with an offset-detector geometry, I directly registered it to the current image space. However, when the prior image was obtained with a different geometry, such as planning CT geometry, I also shifted the image before registration for accommodating it to the current offset-detector geometry. Results show that appropriately incorporated prior image can improve the convergence efficiency, lower the minimum required number of projections, and increase the upper bound of allowable degree of data truncation at each view without compromising accurate image reconstruction.

1.8 Evaluate reconstructed images with quantitative metrics

I have carried out for each simulated and real data experiment an evaluation study by calculating relevant quantitative metrics. Depending on the nature of these metrics, current effort on image-quality evaluation has been classified to similarity-metric-based evaluation and technical-efficacy-metric-based evaluation.

Similarity-metric-based evaluation I have computed quantitative metrics, including root-mean-squared error (RMSE), mutual information (MI), and universal quality index (UQI) [27] for characterizing the similarity between the designed and desired solutions. For innovative imaging configurations including sparse-view and narrow-beam illumination, the reconstructed images (i.e., designed solutions) have been compared with the images reconstructed from full-view data or data without truncation. Specifically, the impact of optimization-program parameters and algorithm parameters have been characterized by plotting these metrics versus the parameter values.

Technical-efficacy-metric-based evaluation I also computed technical-efficacy-based metrics, such as spatial resolution, contrast-noise-ratio (CNR), and detectability, for both designed and desired solutions. Due to different image texture, some metrics computed from sparse-view or truncated reconstruction can be comparable or even higher than those computed from the desired reconstruction. These metrics, however, generally decrease when the number of view decreases, or when the truncated region increases. I have therefore determined the lower bound of view reduction and upper bound of degree of truncation when the corresponding aspect of image quality falls below that computed from the desired solution.

KEY RESEARCH ACCOMPLISHMENTS

- I have investigated and implemented reverse-helix and two-circle scanning trajectories and have obtained real data from a clinical CBCT system with these trajectories.
- I have acquired real data of physical phantom on a clinical CBCT system under full-view, sparse-view, data truncation, and offset-detector configurations.
- I have investigated and developed optimization-based algorithms for CBCT reconstruction by specifying imaging model, formulating optimization programs, and designing and implementing iterative algorithms.
- I have carried out numerical validation studies to verify the iterative algorithms for their capability of reaching the designed solution, and to verity the optimization programs for their capability of yielding designed solution close to the desired solution.
- I have reconstructed CBCT images from full-view data acquired at current clinical configurations and showed potential quality improvement by use of prior-image incorporated, optimization-based algorithms.
- I have reconstructed CBCT images from sparse-view data and showed that images comparable to what is currently used can be obtained from low-dose data containing significantly reduced projection views.
- I have reconstructed CBCT images from truncated data and showed that images comparable to what is currently used can be obtained from low-dose data containing severe truncation.
- I have reconstructed CBCT images from offset-detector data and showed that current CBCT FOV can be enlarged without introducing additional artifacts.
- I have carried out quantitative characterization and evaluation studies by calculating similarity-based and technical-efficacy-based metrics.

REPORTABLE OUTCOMES

Peer-reviewed Journal Papers

1. **X. Han**, J. Bian, E. L. Ritman, E. Y. Sidky, and X. Pan, “Optimization-based reconstruction of sparse images from few-view projections,” *submitted to Physics in Medicine and Biology (under revision)*
2. J. Bian, J. Wang, **X. Han**, E. Y. Sidky, L. Shao, and X. Pan, “Optimization-based image reconstruction from sparse-view data in offset-detector CBCT,” *submitted*
3. D. Xia, X. Xiao, J. Bian, **X. Han**, E.Y. Sidky, F. De Carlo, and X. Pan, “Image Reconstruction from sparse data in synchrotron-radiation-based micro-tomography,” *Review of Scientific Instruments* vol. 82 (4), 2011.
4. **X. Han**, J. Bian, D. R. Eaker, T. L. Kline, E. Y. Sidky, E. L. Ritman, and X. Pan, “Algorithm-enabled low-dose micro-CT imaging,” *IEEE Transactions on Medical Imaging*, vol. 30 (3), pp 606-620. **(According to ieeexplore.ieee.org, this article became one of the top five most accessed articles of *IEEE Transactions on Medical Imaging* immediately after its publication (March, 2011))**
5. J. Bian, J. H. Siewerdsen, **X. Han**, E. Y. Sidky, J. L. Prince, C. A. Pelizzari, and X. Pan,“Evaluation of sparse-view reconstruction from flat-panel-detector cone-beam CT,” *Physics in Medicine and Biology*, vol. 55, pp 6575-6599, 2010. **(Featured article of *Physics in Medicine and Biology*, published online on Oct-20, 2010, one of the ten most read articles of the journal a few days after its publication until now (Feb-2011), was selected as part of the journal’s highlights collection of 2010, cover story of Medicalphysicsweb Review of winter 2011, one of the ten candidates of Roberts’ Prize for best paper in *Physics in Medicine and Biology* and the results will be announced in September, 2011.)**

Conference Proceeding Articles

1. Z. Zhang, **X. Han**, J. Bian, D. Shi, A. Zamyatin, E. Y. Sidky, and X. Pan, “Initial experience in constrained-TV-minimization image reconstruction from diagnostic-CT Data,” Proceedings of the 2nd International Conference on Image Formation in X-ray Computed Tomography, 2012
2. Z. Zhang, J. Bian, **X. Han**, D. Shi, A. Zamyatin, E. Y. Sidky, and X. Pan, “Iterative image reconstruction with variable resolution in diagnostic CT,” Proceedings of the 2nd International Conference on Image Formation in X-ray Computed Tomography, 2012
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5. J. Bian, **X. Han**, K. Yang, E. Y. Sidky, J. M. Boone, and X. Pan, “A preliminary study of image reconstruction from low-dose data in dedicated breast CT,” IEEE Nucl. Sci. Conf. Rec., 2011

6. J. Bian, J. Wang, **X. Han**, E. Y. Sidky, J. Ye, S. Prevrhal, H. Liang, L. Shao, and X. Pan, "Sparse-view image reconstruction from gated cardiac data," IEEE Nucl. Sci. Conf. Rec., 2011

7. Z. Zhang, **X. Han**, J. Bian, J. J. Manak, E. Y. Sidky, and X. Pan, "Initial experience in image reconstruction from limited-angle C-arm CBCT data," IEEE Nucl. Sci. Conf. Rec., 2011

8. Z. Zhang, J. Bian, **X. Han**, E. Pearson, E. Y. Sidky, and X. Pan, "Iterative image reconstruction with variable resolution in CT," IEEE Nucl. Sci. Conf. Rec., 2011

9. **X. Han**, S. Shi, J. Bian, P. Helm, E. Y. Sidky, and X. Pan, "Feasibility study of low-dose intra-operative cone-beam CT for image-guided surgery," Proc. SPIE, 7961, 79615P, 2011

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11. **X. Han**, J. Bian, D. R. Eaker, T. L. Kline, E. Y. Sidky, E. L. Ritman, and X. Pan, "Image reconstruction from a reduced number of projections in micro-CT specimen imaging," IEEE Nucl. Sci. Conf. Rec., 2010

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13. X. Xiao, D. Xia, J. Bian, **X. Han**, E. Y. Sidky, F. De Carlo, and X. Pan, "Image reconstruction from sparse data in synchrotron-based micro-tomography of biomedical samples," Proceedings of the First International Conference on Image Formation in X-ray Computed Tomography, 2010

14. J. Bian, J. Wang, **X. Han**, E. Y. Sidky, J. Ye, L. Shao, and X. Pan, "Reconstruction from sparse data in offset-detector CBCT," Proceedings of the First International Conference on Image Formation in X-ray Computed Tomography, 2010

15. D Xia, J. Bian, **X. Han**, E. Y. Sidky, J. Lu, O. Zhou, and X. Pan, "Investigation of image reconstruction in CT with a limited number of stationary sources," Proceedings of the First International Conference on Image Formation in X-ray Computed Tomography, 2010

16. **X. Han**, J. Bian, D. R. Eaker, E. Y. Sidky, E. L. Ritman, and X. Pan, "A preliminary study of few-view image reconstruction of sparse objects in cone-beam micro-CT," Proc. SPIE, 7622-96, 2010

Conference Presentations and Abstracts

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2. **X. Han**, J. Bian, D. R. Eaker, E. Y. Sidky, E. L. Ritman, and X. Pan, "An investigation on image reconstruction of coronary arteries from few-View Data," IEEE Medical Imaging Conference, Valencia, Spain, October 2011

3. E. Pearson, **X. Han**, X. Pan, and C. A. Pelizzari, “Iterative Reconstruction for Axial Field of View Extension in Radiotherapy Cone-Beam CT,” IEEE Medical Imaging Conference, Valencia, Spain, October 2011
4. J. Bian, **X. Han**, K. Yang, E. Y. Sidky, J. M. Boone, and X. Pan, “A preliminary study of image reconstruction from low-dose data in dedicated breast CT,” IEEE Medical Imaging Conference, Valencia, Spain, October 2011
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CONCLUSIONS

During the second year of the project, I have investigated and implemented novel scanning trajectories with aid of additional hardware components and software control. Simulation data have been generated for initial test of object coverage for these scanning trajectories. I have also acquired real data of physical phantoms by using a clinical CBCT system under a variety of sampling configurations, including full-view, sparse-view, truncated data, and offset-detector configurations. I carried out a rigorous investigation on developing optimization-based image reconstruction algorithms by specifying a discrete imaging model, formulating optimization programs, and designing and implementing iterative algorithms. I have designed a host of parameters for the imaging model, optimization programs, and iterative algorithms, and strategies for adaptively selecting these parameters have been laid out. I have used developed optimization-based algorithms to reconstruct images from data acquired under various sampling configurations. Prior images have been investigated for incorporation in image reconstruction tasks for all the data acquisition configurations. Quantitative metrics have been calculated for quantitatively characterizing and evaluating the reconstruction quality, choice of parameters, and strategies for incorporating prior images.

In summary, I have achieved the goals planned for the second year, which have laid down the foundation for the research in the next year. The aims in the next year include further development of the prior image-based, narrowly collimated CBCT imaging technique, prior image-based, sparse-view CBCT imaging technique, and characterization and evaluation of the proposed configurations and algorithms by using physical phantoms and patient data.

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